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Modelling Stock Market Volatility Using Univariate GARCH Models: Evidence from Sudan and Egypt

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Abstract

Stock market volatility in two African exchanges, Khartoum Stock Exchange, KSE (from Sudan) and Cairo and Alexandria Stock Exchange, CASE (from Egypt) is modelled and estimated. The analysis is based on using daily closing prices on the general indices in the two markets over the period of 2nd January 2006 to 30th November 2010. The paper employs different univariate specifications of the Generalized Autoregressive Conditional Heteroscedastic (GARCH) model, including both symmetric and asymmetric models. The empirical results show that the conditional variance (volatility) is an explosive process for the KSE index returns series, while it is quite persistent for the CASE index returns series. The results also provide evidence on the existence of a positive risk premium in both markets, which supports the hypothesis of a positive correlation between volatility and the expected stock returns. Furthermore, the asymmetric GARCH models find a significant evidence for asymmetry in stock returns in the two markets, confirming the presence of leverage effect in the returns series.

Keywords: volatility, stock returns, GARCH models, heteroscedasticity, volatility clustering, leverage effect

1. Introduction

Over the last few years, modelling and forecasting volatility of financial time series (i.e. asset returns) has become a fertile area of research in finance, and has been receiving considerable attention from academics and practitioners. This is because volatility is an important concept for many economic and financial applications, like portfolio optimization, risk management and asset pricing. A special feature of volatility, which according to Tsay (2010) is "the conditional variance of the underlying asset returns", is that it is not directly observable. Consequently, financial analysts are especially keen to obtain good estimates of this conditional variance in order to improve portfolio allocation, risk management or valuation of financial derivatives. Since the 1980s a number of models has been developed that are especially suited to estimate the conditional volatility of financial assets. Well-known and frequently applied models of this type are the (generalized) conditional heteroscedastic models.

Among these models, the Autoregressive Conditional Heteroscedastic (Note 1) (ARCH) model proposed by Engle (1982) and its extension, the Generalized Autoregressive Conditional Heteroscedastic (GARCH) model developed independently by Bollerslev (1986), and Taylor (1986) have been the first models introduced into the literature and have become very popular (Enders, 2004). Since then, there have been a great number of empirical applications of modelling the conditional variance (volatility) of financial time series by employing different specifications of these models and their many extensions (Note 2). For example, Chou (1988), Nelson (1991), Bollerslev et al. (1992), Engle and Patton (2001), and Brooks and Burke (2003) provide an extended methodological framework that can be applied to various problems in finance. On the empirical level, several applications have been found on both developed and developing stock markets, see for example De Santis and Imrohoroglu (1997), Husain and Uppal (1999), Bekaert and Wu (2000), McMillan et al. (2000), Engle and Patton (2001), Poshakwale and Murinde (2001), Brooks and Burke (2003), Balaban et al. (2004), Ogum et al. (2005), Shin (2005), Chukwuogor (2006), Bali (2007), Edel and Brian (2007), Floros (2007), Leaon (2007), Ocran and Biekets (2007), Alberg et al. (2008), Samouilhan and Shannon (2008), Shamiri and Isa (2009), Olowe (2009), Kalu (2010) and Mishra (2010)). These models were designed to explicitly model and forecast the time-varying conditional second order moment (variance) of a series by using past unpredictable changes in the returns of that series, and have been applied successfully in economics and finance, but more predominantly in financial market research. For the case of Egypt there are some studies concerned with the issue of modelling stock market volatility (see for example Tooma (2003), Mecagni and Sourial (1999), Ebeid and Bedeir (2004), and Floros (2008)), but to the best of our knowledge, there are no such empirical studies for the Sudanese stock market. Thus, one of the contributions of this paper is to provide empirical evidence on the fit of conditional volatility models for the Sudanese stock market.

The main objective of this paper is to model stock returns volatility in two African markets; the Sudanese stock market (Khartoum Stock Exchange, KSE), and the Egyptian stock market (Cairo and Alexandria Stock Exchange, CASE) by employing different univariate specifications of GARCH type models for daily observations on the index returns series of each market over the period of 2nd January 2006 to 30th November 2010, as well as describing special features of the markets in terms of trading activity and index components and calculations. The volatility models employed in this paper include both symmetric and asymmetric GARCH models. While the CASE might be considered as one of the most advanced stock markets within the African continent, the KSE has been established only recently and exhibits a limited track record. Therefore, it might be of particular interest to compare the volatility on both markets.

The remaining of this paper is organized as follows: Section 2 provides a general overview of the stock exchange in Sudan and Egypt. Section 3 describes the data and provides summary statistics. In the fourth section the GARCH methodology is presented, while the estimations results are discussed in Section 5. Finally, Section 6 concludes the paper.

2. Literature Review

There has been a large amount of literature on modelling and forecasting stock market volatility in both developed and developing countries around the world. Many econometric models have been used to investigate volatility characteristics. However, no single model is superior. Pindyck (1984) demonstrates that the increases in variance of stock returns can explain much of the decline in stock prices. Whitelaw (1994) offers empirical evidence for a positive relation between a lagged volatility measure and future expected returns. For Asian stock markets, Koutmos (1999) and Koutmos and Saidi (1995) found that the conditional variance is an asymmetric function of past innovations. Positive past returns are on average 1.4 times more persistent than negative past returns of an equal magnitude. Lee et al. (2001) examined time-series features of stock returns and volatility in four of China's stock exchanges. They provided strong evidence of time-varying volatility and indicated volatility is highly persistent and predictable. Moreover, evidence in support of a fat-tailed conditional distribution of returns was found. By employing eleven models and using symmetric and asymmetric loss functions to evaluate the performance of these models, Balaban, Bayar, and Faff (2003) forecasted stock market volatility of fourteen stock markets. According to symmetric loss functions the exponential smoothing model provides the best forecast. However, when asymmetric loss functions are applied ARCH-type models provide the best forecast. Balaban and Bayar (2005) used both symmetric and asymmetric ARCH-type models to derive volatility expectations. The outcome showed that there has a positive effect of expected volatility on weekly and monthly stock returns of both Philippines and Thailand markets according to ARCH model. The result is not clear if using the other models such as GARCH, GJR-GARCH and EGARCH. For emerging African markets, Ogum, Beer and Nouyrigat (2005) investigate the market volatility using Nigeria and Kenya stock return series. Results of the exponential GARCH model indicate that asymmetric volatility found in the U.S. and other developed markets is also present in Nigerian stock exchange (NSE), but Kenya shows evidence of significant and positive asymmetric volatility. Also, they show that while the Nairobi Stock Exchange return series indicate negative and insignificant risk-premium parameters, the NSE return series exhibit a significant and positive time-varying risk premium. By using asymmetric GARCH models, Alberg et al. (2006) estimate stock market volatility of Tel Aviv Stock Exchange indices, for the period 1992-2005. They report that the EGARCH model is the most successful in forecasting the TASE indices. Various time series methods are employed by Tudor (2008), including the simple GARCH model, the GARCH-in-Mean model and the exponential GARCH to investigate the Risk-Return Trade-off on the Romanian stock market. Results of the study confirm that E-GARCH is the best fitting model for the Bucharest Stock Exchange composite index volatility in terms of sample-fit.

3. Overview of Stock Market in Sudan and Egypt

3.1 Sudanese Stock Market

The Khartoum Stock Exchange (KSE) is the principal stock exchange of Sudan located in Khartoum. The KSE started its activities officially in January 1995 with the assistance of the Common Market for Eastern and Southern Africa (CoMESA) (Note 3), with the objective of regulating and controlling the issuance of securities, and mobilizing private savings for investment in securities. Securities traded in the KSE are ordinary shares and investment units (Note 4). Furthermore, a substantial number of mutual funds and Government Investment Certificates (GICs) (Note 5) are also traded (KSE Annual report, 2010). Orders are handled through brokers during trading hours and share prices are quoted in Sudanese Pound (SDG). Trading is processed manually by continuous auction from Sunday to Thursday for one hour from 10.00 am to 11.00 am. Thereby, buy and sell orders are passed on to floor-based representatives of registered brokers for execution. Trading in securities is taking place in two markets, the so called primary and secondary markets (Note 6).

As a part of the financial system of Sudan, KSE operates on the basis of Islamic Shariaa and is supervised and regulated by the Central Bank of Sudan (Note 7). The key feature of Islamic Shariaa practices in Khartoum Stock Exchange is that it is aimed to offer investment portfolios from common stocks of listed companies which ideally satisfy three basic criteria: (i) legitimate field of economic activity; (ii) interest-free dealings in both assets and liabilities, and (iii) the dominance of real assets. Thus, e.g., a company must not be engaged in the production of illegitimate goods like alcoholic drinks; it must not deal with interest rate financing as a means to leverage its capital structure through fixed debt liabilities, or generate interest income from investment securities; and since a company's shares represent equity rights in its assets, the latter should be real assets, not liquid money or receivable debt as they cannot be sold freely at a profit like real goods, real estate and machinery (Hassan and Lewis, 2007).

As consequences of these rules, the composition of assets traded at the KSE differs substantially from other stock markets. In particular, due to the regulations imposed by Islamic Shariaa (Note 8) practices a separate class of investment vehicles on the KSE is provided by the so called Government Musharakah (Note 9) Certificates (GMCs), which represent an Islamic equivalent to conventional bonds (also known as Shahama bonds). Shahama bonds offer a way for the government to borrow money in the domestic market instead of printing more banknotes. After one year, holders of GMCs can either liquidate them or extend their duration. These bonds are backed by the stocks of various companies owned by the Ministry of Finance. Consequently, they might be considered as asset-backed securities. The profitability of GMCs depends on the financial results of the companies in the underlying portfolio. It can reach up to 33 per cent per annum. Hence, the profit of GMCs is variable rather than fixed. The government issues these bonds on a quarterly basis and their placement on the market is done usually very fast- in just six days.

The overall performance of the Khartoum stock market is measured by the KSE Index, which is a market capitalization-weighted index. In September 2003, the KSE index was established and listed in the Arab Monetary Fund database. At the end of the first month the index closed at 961.74 points. In December 2005, the index closed at the highest level of 3259.17 points. In November 2010, it was fluctuating around an average value of 2365.66.

3.2 Egyptian Stock Market

In contrast to the KSE, the Egyptian exchange is one of the oldest stock markets established in the Middle East and Africa. Egypt's stock exchange has two locations: the main location is in Cairo (established 1903) and the other one is in Alexandria (established 1883).These two exchanges were competing with each other before they merged in recent years. Today, both exchanges are governed by the same chairman and board of directors. They are commonly referred to as the Cairo and Alexandria Stock Exchange (CASE) and share the same trading, clearing and settlement systems, so that market participants have access to stocks listed on both exchanges.

The overall performance of the Egyptian stock market is measured by the Capital Market Authority (CMA) Index, which covers all listed stocks weighted in relation to their market capitalization. It can be viewed as an all share index that covers the broadest base of stocks. It is calculated and released daily by the CMA (Note 10).

3.3 Key Numbers of the KSE and CASE

Table 1 provides some key figures of both exchanges. It is obvious that considering any of the indicators used like number of listed companies or market capitalization, the Khartoum stock exchange represents a much smaller market compared to the Cairo and Alexandria stock exchange. While the number of listed companies comes close to one quarter of the CASE in 2012, the number of transactions falls short of 0.1 percent and market capitalization is below 5 percent of the corresponding values of CASE. The relatively large number of listed companies at the KSE appears to be due rather to a massive decline of the number of listed companies on the CASE since 2006 than to an increase of activities on the KSE. Considering the volume of trading relative to market capitalization, both markets exhibit some similarities, i.e. the yearly trading volume reaches about 30 percent of market capitalization in recent years.

Table 1. Summary of Trading Activity in KSE and CASE, 2006 – 2010

	No. Of Listed companies*		No. Of traded shares (In Million)		Volume of trading ($ millions)		No. of transactions		Market Capitalization ($ millions)	
	KSE	CASE	KSE	CASE	KSE	CASE	KSE	CASE	KSE	CASE
2006	52	595	7,567.78	NA	833.89	NA	5,842	NA	3,912.61	NA
2007	53	435	9,411.56	10,512.79	749.58	49,388.19	7,195	8,161,607	4,048.64	134,903.52
2008	53	373	289.00	21,071.82	751.60	65,166.14	8,177	12,321,523	3,416.60	83,185.00
2009	53	306	164.71	28,243.25	891.27	50,812.70	8,069	13,300,653	2,784.76	86,267.22
2010	53	212	166.55	27,336.99	972.69	36,867.80	8,266	9,606,668	3,166.89	85,725.96

Source: Compiled by the authors based on data from the KSE website and AMF annual reports.

4. Research Methods

Autoregressive conditional heteroscedasticity (ARCH) (Note 12) and its generalization (GARCH) models represent the main methodologies that have been applied in modelling and forecasting stock market volatility (Note 13) in empirical finance. In this paper different univariate GARCH specifications are employed to model stock returns volatility in Khartoum stock exchange and Cairo and Alexandria stock exchange, these models are GARCH (1,1), GARCH-M (1,1), which will be used for testing symmetric volatility and EGARCH(1,1), TGARCH(1,1) and PGARCH (1,1) for modelling asymmetric volatility (Note 14). These models will be shortly discussed in the following subsections. For all these different models, there are two distinct equations, the first one for the conditional mean and the second one for the conditional variance. We are mainly interested in the second equation as it provides estimates and conditional forecast of volatility.

4.1 Symmetric GARCH Models

4.1.1 The Generalized Autoregressive Conditional Heteroscedastic (GARCH) Model

In this model, the conditional variance is represented as a linear function of a long term mean of the variance, its own lags and the previous realized variance. The simplest model specification is the GARCH (1,1) model:

Mean equation $$r_t = \mu + \varepsilon_t \ , \tag{1}$$

Variance equation $$\sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \tag{2}$$

where $\omega > 0$, $\alpha_1 \geq 0$ and $\beta_1 \geq 0$, and:

r_t = return of the asset at time t,

μ = average return,

ε_t = residual returns, defined as:

$$\varepsilon_t = \sigma_t z_t \tag{3}$$

where z_t are standardized residual returns (i.e. realization of an iid random variable with zero mean and variance 1), and σ_t^2 stands for the conditional variance. For GARCH (1,1), the constraints $\alpha_1 \geq 0$ and $\beta_1 \geq 0$ are needed to ensure that σ_t^2 is strictly positive (Poon, 2005). The conditional variance equation models the time varying nature of volatility of the residuals generated from the mean equation. This specification is often interpreted in a financial context, where an agent or trader predicts this period's variance by forming a weighted average of a long term average (the constant), the forecast variance from last period (the GARCH term), and information about volatility observed in the previous period (the ARCH term). If the asset return was unexpectedly large in either the upward or the downward direction, then the trader will increase the estimate of the variance for the next period, while the GARCH-term generates persistence of volatility.

4.1.2 The Generalized Autoregressive Conditional Heteroscedastic-in-Mean (GARCH-M) Model

In finance, the return of a security may depend on its volatility. To model such a phenomenon one may consider the GARCH-M model developed by of Engle, Lilien, and Robins (1987), where "M" stands for GARCH in the mean (Tsay 2010). This model is an extension of the basic GARCH framework which allows the conditional mean of a sequence to depends on its conditional variance or standard deviation. A simple GARCH -M(1,1) model can be written as :

Mean equation $$r_t = \mu + \lambda\sigma_t^2 + \varepsilon_t \tag{4}$$

Variance equation $$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 \tag{5}$$

The parameter λ in the mean equation is called the risk premium parameter. A positive λ indicates that the return is positively related to its volatility. In other words, a rise in mean return is caused by an increase in conditional variance as a proxy of increased risk. Engle, Lilien, and Robins assume that the risk premium is an increasing function of the conditional variance of ε_t; in other words, the greater the conditional variance of returns, the greater the compensation necessary to induce the agent to hold the asset (Enders 2004).

4.2 Asymmetric GARCH Models

An interesting feature of asset prices is that bad news seems to have a more pronounced effect on volatility than do good news. For many stocks, there is a strong negative correlation between the current return and the future volatility. The tendency for volatility to decline when returns rise and to rise when returns fall is often called the leverage effect (Enders, 2004).

The main drawback of symmetric GARCH models is that the conditional variance is unable to respond asymmetrically to rises and falls in ε_t, and such effects are believed to be important in the behaviour of stock returns. In the linear GARCH (p,q) model the conditional variance is a function of past conditional variances and squared innovations; therefore, the sign of returns cannot affect the volatilities (Knight and Satchell, 2002). Consequently, the symmetric GARCH models described above cannot account for the leverage effect observed in stock returns, consequently, a number of models have been introduced to deal with this phenomenon. These models are called asymmetric models. This paper uses EGARCH, TGARCH and PGARCH for capturing the asymmetric phenomena.

4.2.1 The Exponential Generalized Autoregressive Conditional Heteroscedastic (EGARCH) Model

This model captures asymmetric responses of the time-varying variance to shocks and, at the same time, ensures that the variance is always positive. It was developed by Nelson (1991) with the following simple specification:

$$Ln(\sigma_t^2) = \omega + \beta_1 Ln(\sigma_{t-1}^2) + \alpha_1\left\{\left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right| - \sqrt{\frac{2}{\pi}}\right\} - \gamma\frac{\varepsilon_{t-1}}{\sigma_{t-1}} , \tag{6}$$

where γ is the asymmetric response parameter or leverage parameter. The sign of γ is expected to be positive in most empirical cases so that a negative shock increases future volatility or uncertainty while a positive shock eases the effect on future uncertainty (Note 15).

4.2.2 The Threshold Generalized Autoregressive Conditional Heteroscedastic (TGARCH) Model

Another volatility model commonly used to handle leverage effects is the threshold GARCH (or TGARCH) developed by Zakoian (1994). In the TGARCH (1,1) version of the model, the specification of the conditional variance (Note 16) is:

$$\sigma_t^2 = \omega + \alpha_1\varepsilon_{t-1}^2 + \gamma d_{t-1}\varepsilon_{t-1}^2 + \beta_1\sigma_{t-1}^2 , \tag{7}$$

where d_{t-1} is a dummy variable, that is:

$$d_{t-1} = \begin{cases} 1 & if \quad \varepsilon_{t-1} \prec 0, \quad bad \quad news \\ 0 & if \quad \varepsilon_{t-1} \geq 0, \quad good \quad news \end{cases} \tag{8}$$

Again, the coefficient γ is known as the asymmetry or leverage parameter. When $\gamma = 0$, the model collapses to the standard GARCH forms. Otherwise, when the shock is positive (i.e., good news) the effect on volatility is α_1, but when the news is negative (i.e., bad news) the effect on volatility is $\alpha_1 + \gamma$. Hence, if γ is significant and positive, negative shocks have a larger effect on σ_t^2 than positive shocks (Carter, 2007).

4.2.3 The Power Generalized Autoregressive Conditional Heteroscedastic (PGARCH) Model

Ding, Granger and Engle (1993) also introduced the Power GARCH (PGARCH) specification to deal with asymmetry. Unlike other GARCH models, in this model, the standard deviation is modelled rather than the variance as in most of the GARCH-family. In Power GARCH an optional parameter γ can be added to account for asymmetry (Floros, 2008). The model also offers one the opportunity to estimate the power parameter δ instead of imposing it on the model (Ocran and Biekets, 2007).

The general asymmetric Power GARCH model specifies σ_t as of the following form:

$$\sigma_t^{\delta} = \omega + \beta_1 \sigma_{t-1}^{\delta} + \alpha_1 (|\varepsilon_{t-1}| - \gamma_1 \varepsilon_{t-1})^{\delta} \tag{9}$$

where α_1 and β_1 are the standard ARCH and GARCH parameters, γ_1 is the leverage parameter and δ is the parameter for the power term. When $\delta = 2$, equation (9) becomes a classic GARCH model that allows for leverage effects, and when $\delta = 1$, the conditional standard deviation will be estimated. It is possible to increase the flexibility of the PGARCH model by considering δ as another coefficient that also has to be estimated (see Zivot 2008).

5. Data and Empirical Results

5.1 The Data and Basic Statistics

5.1.1 The Data Used for the Analysis

The time series data used for modelling volatility in this paper are the daily closing prices of the Khartoum Stock Exchange (KSE) index and the Capital Market Authority (CMA) index over the period from 2nd January 2006 to 30th November 2010, resulting in a total of 1326 observations for the KSE index and 1287 for the CMA index excluding public holidays. These closing prices have been taken from the KSE website (http://www.kse.com.sd) and the CASE website (http://www.egyptse.com).

Daily returns r_t were calculated as the continuously compounded returns corresponding to the first difference in logarithms of closing prices of successive days:

$$r_t = \log\left(\frac{P_t}{P_{t-1}}\right) \tag{10}$$

where P_t and P_{t-1} denote the closing market index of KSE and CASE at the current (t) and previous day (t-1), respectively.

It is very important to note that since October 18, 2009, the index on the Khartoum Stock Market has been declining. In only 16 trading days, the stock market index fell from 3077.12 October 18, 2009 to 2363.30 on November 10, 2009. Since that time, the KSE index was reporting to fluctuate around an average value of 2363.23. In order to see the impact of this sharp fall on the volatility modeling, the full data set is divided into two sub-periods: the first sub-period covers Jan. 2, 2006 to Oct. 18, 2009 with 1042 total observations, while the second sub-period ranges from Nov. 10, 2009 to Nov. 30 2010 resulting in 269 observations. So, the results will be presented separately for three periods; for the period before the sharp fall, the period after that fall and for the whole data set.

5.1.2 Descriptive Statistics of KSE and CASE Returns Series

To specify the distributional properties of the daily returns series in KSE and CASE markets during the period of this study, some descriptive statistics are reported in Table 2.

Table 2. Descriptive statistics of the KSE and CMAI return series

Statistics	**KSE return series**			**CMAI return series**
	First sub-period	Second sub-period	Full sample period	
Mean	0.01%	0.00%	-0.02%	0.01%
Median	0%	0%	0.00%	0.01%
Maximum	21%	1%	21.12%	6.55%
Minimum	-11%	-1%	-11.61%	17.43%
Standard Deviation	1.47%	0.71%	1.37%	1.83%
Skewness	2.57	3.52	1.76	-1.17
Kurtosis	65.31	82.71	73.72	11.59
Jarque-Bera	169550.4	71496.33	276573.2	4246.72
Prob. of Jarque-Bera	0.000	0.000	0.000	0.000
No. of observations	1042	269	1326	1287

Sample period: January 2, 2006 – November 30, 2010.

As we can see from Table 2, the average returns for the CMA index is higher than the average of the KSE index. The distribution of returns differs markedly from normality given the observed skewness and excess kurtosis. Consequently, based on the Jarque-Bera (J-B) statistic, the null hypothesis of normality for the daily KSE and CASE returns has to be rejected at the 1% significance level. Moreover, Figure 1 presents the pattern of the price index series and its returns for the CASE and the KSE during the study period.

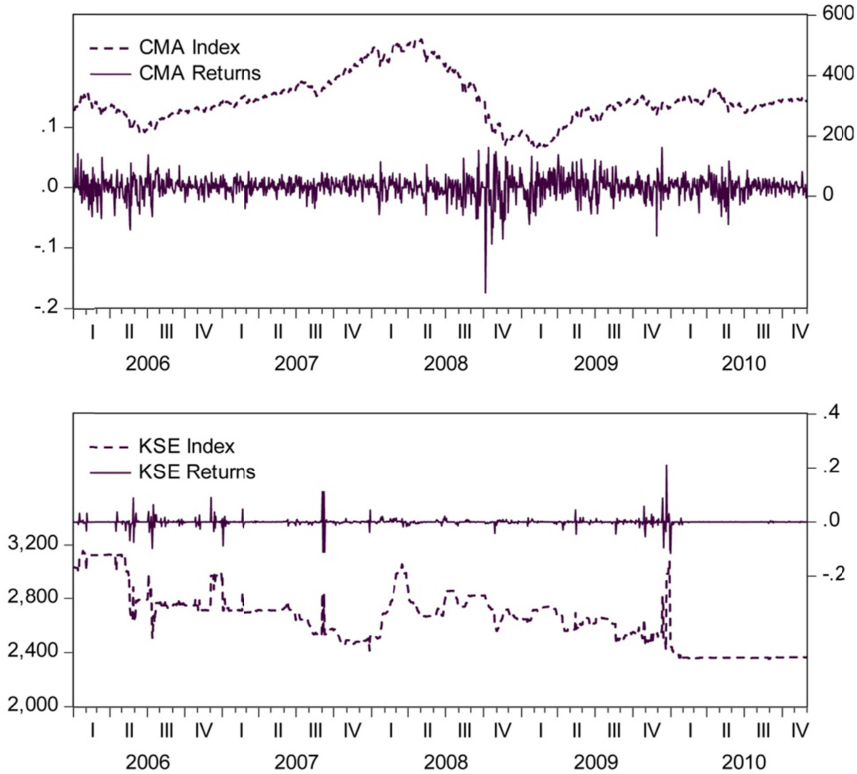

Figure 1. Daily prices and returns for the CMA and KSE indices (Jan. 2006 – Nov. 2010)

While the time series for CMA (upper part) resemble qualitatively those found for other stock exchanges, the time series for KSE exhibit different patterns. In particular, the dependence in the volatility of returns as shown in Figure 1 (lower part) appears much more pronounced, at least up to the end of 2009. Afterwards, the price series becomes almost flat with very small returns. We will consider this obvious structural break in our empirical analysis although it turned out to be difficult to identify a specific reason for this change.

5.1.3 Quantile-Quantile (Q-Q) Plots

As a further instrument for analyzing the distributional properties, we apply the Q-Q graphical examination to check whether the KSE index and CMA index returns series are normally distributed. The Q-Q plot is a scatter plot of the empirical quantiles (vertical axis) against the theoretical quantiles (horizontal axis) of a given distribution (Alexander, 2001). If the sample observations follow approximately a normal distribution with mean equal to the empirical mean (μ) and standard deviation equal to the empirical standard deviation σ , then the resulting plot should be roughly scattered around the 45-degree line with a positive slope. The greater the departure from this line, the greater the evidence against the null hypothesis of a normal distribution. The results of this graphical examination are provided in Figure 2.

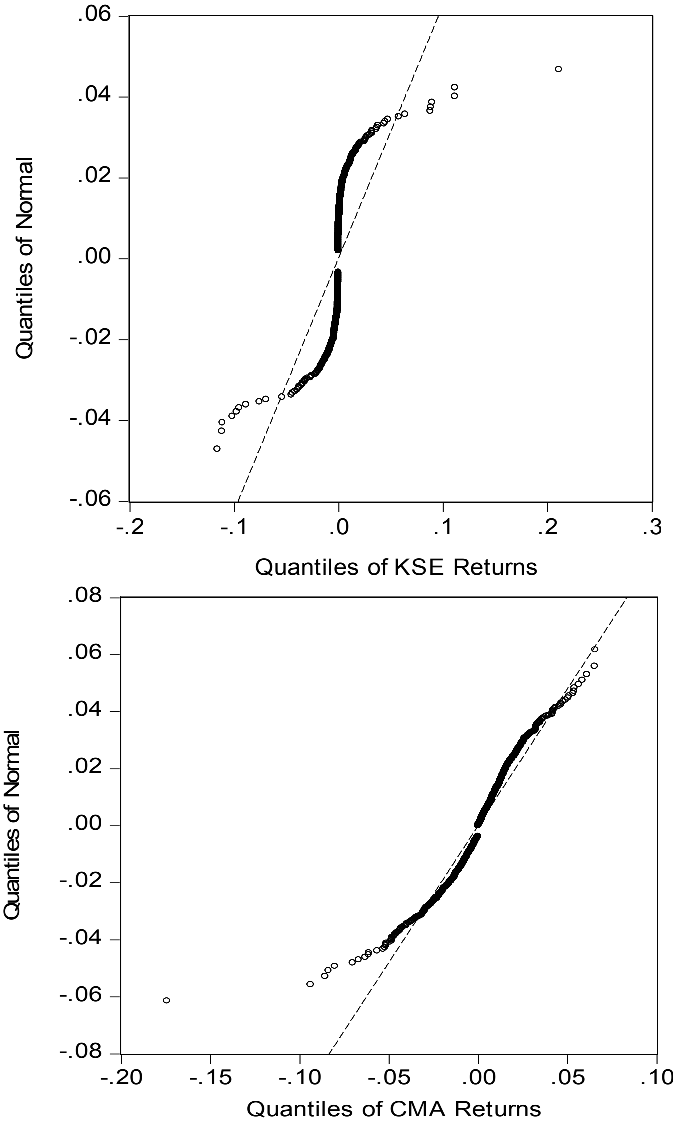

Figure 2. Normal Quantile-Quantile Plots for the Daily Stock Returns 2006 – 2010

The QQ-plot in Figure 2 confirms the findings from Table 2 that the KSE and CASE returns data do not follow a distribution similar to a normal distribution.

5.1.4 Testing for Stationarity

To investigate whether the daily price index and its returns are stationary series, the Augmented Dickey–Fuller (ADF) test (Dickey and Fuller, 1981) has been applied. Thereby, the lag length has been selected automatically based on the Schwarz information criterion with a preset maximum lag length of 22. The results are reported in Table 3.

Table 3. ADF unit root test output for the price index and returns series in KSE and CASE

ADF unit root test for the price index series					
Index		**ADF statistic**	**Critical values**		
			1%	**5%**	**10%**
KSE index	First sub-period	-2.671(5)*	-3.436	-2.864	-2.568
	Second sub-period	-7.469(0)**	-3.455	-2.872	-2.572
	Full period	-2.390(6)	-3.438	-2.864	-2.568
CMAI		-1.456(1)	-3.435	-2.864	-2.568
ADF unit root test for the return series					
Return		**ADF statistic**	**Critical values**		
			1%	**5%**	**10%**
KSE index return	First sub-period	-29.419(1)**	-3.463	-2.864	-2.568
	Second sub-period	-20.352(2)**	-3.455	-2.872	-2.572
	Full period	-18.590(5)*	-3.438	-2.864	-2.568
CMA index		-30.571(0)*	-3.435	-2.864	-2.568

Notes: 1- Figures in parentheses denote the optimal lag lengths, which were automatically selected based on the Schwarz Information Criterion (SIC).

2- Critical values for unit root tests are taken from MacKinnon (1996).

3- * and ** Indicate that the results are statistically significant at the 1% and 5% levels respectively.

4- ADF test includes a constant term without trend.

Table 3 reports the results of the ADF test for a lag length of 6 and 1 for the two indices in levels and a lag length of 5 and 0 for the two returns series. The ADF tests for the level data indicate that they have to be considered as non-stationary series for both markets (Note 11). When applying the same test for the returns series, the results allow rejecting the null hypothesis of a unit root at all conventional levels of significance for both series. Therefore, we conclude that the returns series might be considered as stationary over the specified period.

5.1.5 Testing for Heteroscedasticity

Given that we are interested in analyzing volatility on both markets, a first step consists in testing for (conditional) heteroscedasticity. To this end we apply the Lagrange Multiplier (LM) test proposed by Engle (1982) to the residuals of simple time series models of the returns.

In summary, the test procedure is performed by first obtaining the residuals e_t from the ordinary least squares regression of the conditional mean equation which might be an autoregressive (AR) process, moving average (MA) process or a combination of AR and MA processes, i.e. an ARMA process. For example, in the ARMA (1,1) process the conditional mean equation will be:

$$r_t = \phi_1 r_{t-1} + \varepsilon_t + \theta_1 \varepsilon_{t-1} \quad . \tag{11}$$

After obtaining the residuals e_t, the next step consists in regressing the squared residuals on a constant and q lags as in the following equation:

$$e_t^2 = \alpha_0 + \alpha_1 e_{t-1}^2 + \alpha_2 e_{t-2}^2 + ... + \alpha_q e_{t-q}^2 + \nu_t \tag{12}$$

The null hypothesis that there is no autoregressive conditional heteroscedasticity (ARCH) up to order q can be formulated as:

$$H_0 : \alpha_1 = \alpha_2 .. = \alpha_q = 0$$

against the alternative:

$$H_1 : \alpha_i > 0$$

for at least one i = 1, 2, …, q.

The test statistic for the joint significance of the q-lagged squared residuals is given by the number of observations times the R-squared (TR^2) of the regression (12). TR^2 is evaluated against the $\chi^2(q)$ distribution. This represents an asymptotically locally most powerful test (Rachev et al., 2007, 294).

In our case, we first employ an autoregressive moving average ARMA (1,1) model for the conditional mean in the returns series as an initial regression, then, test the null hypothesis that there are no ARCH effects in the residual series up to lag 5 corresponding to one trading week. The results of this examination are summarized in Table 4.

Table 4. ARCH-LM Test for residuals of returns on the KSE and CASE markets

	KSE index return	CMAI return
ARCH-LM test statistic	59.872	37.432
Prob. Chi-square (5)	0.0000	0.0000

Note: H_0 : There are no ARCH effects in the residual series.

The ARCH-LM test results in Table 4 provide strong evidence for rejecting the null hypothesis. Rejecting H_0 is an indication of the existence of ARCH effects in the residuals series of the mean equation and therefore the variance of the returns series of KSE and CASE indices are non-constant.

5.2 Empirical Results

As reported in the data description part, when the residuals were examined for heteroscedasticity, the ARCH-LM test provided strong evidence of ARCH effects in the residual series of both markets. To model this conditional heteroscedasticity, we proceed by applying the GARCH models. The results of estimating different GARCH specifications for the KSE index and the CMA index returns are presented in this section. The models are estimated using the maximum likelihood method under the assumption of Gaussian distributed error terms. The log likelihood function is maximized using Marquardt's numerical iterative algorithm to search for optimal parameters (Note 17). To account for the sharp decline of the KSE index in the second half of October 2009, a dummy variable (DUM) will be introduced into the mean equation, which is set equal to 0 for the period before that sharp decline and 1 thereafter. Thus, for the KSE, the mean equation is specified as:

$$\text{Mean equation } r_t = \mu + DUM + \varepsilon_t \quad (13)$$

Beside the estimation output of different GARCH models, diagnostics test results for these models are also provided, in particular for testing whether there are still ARCH effects left in the residuals of the estimated models (Note 18). Table 5 and Table 6 show the parameter estimates of different GARCH models for the returns of the KSE (Full sample period) and CASE indices for the period under study. Estimation results of subperiods for the KSE returns are reported in Table 1 in the Appendix.

Table 5. Estimation results of different GARCH models for Khartoum stock exchange

Coefficients	GARCH (1,1)	GARCH-M (1,1)	EGARCH (1,1)	TGARCH (1,1)	PGARCH (1,1)
			Mean equation		
μ	0.000352	-	-	-	0.000736**
DUM	-0.000316**	-0.000194	9.27E-05	-0.000223	-0.000759
λ		0.027819	-	-	-
			Variance equation		
ω	2.69E-05*	2.99E-05*	-5.523160*	3.02E-05*	0.000241**
α	0.893622*	0.532562*	0.183655*	0.656067*	0.438671*
β	0.419774*	0.440366*	0.417255*	0.429398**	0.522363*
γ	-	-	-0.017766*	0.189720*	-0.038586
δ	-	-	-	-	1.587719*
$\alpha + \beta$	1.313396	0.972928	0.600910	1.085465	0.961034
Log likelihood	4412.983	4399.383	4059.788	4405.295	4354.494
			ARCH-LM test for heteroscedasticity		
statistic	0.116251	0.086276	27.03379	0.093170	0.236021
Prob.	0.9998	0.9999	0.0001	0.9999	0.9987

Note: * Denotes significance at the 1% level, and ** at 5% level

Table 6. Estimation results of different GARCH models for Egypt stock market

Coefficients	GARCH (1,1)	GARCH-M (1,1)	EGARCH (1,1)	TGARCH (1,1)	PGARCH (1,1)
			Mean equation		
μ	0.000956**	-	0.000652	0.000594	0.000567
λ	-	0.062186**	-	-	-
			Variance equation		
ω	2.38E-06*	2.49E-06*	-0.196748*	3.67E-06*	3.70E-05
α	0.074550*	0.073983*	0.109970*	0.032598*	0.062493*
β	0.921309*	0.921285*	0.986334*	0.917797*	0.932108*
γ	-	-	-0.069011*	0.072128*	0.447800*
δ	-	-	-	-	1.434551*
$\alpha+\beta$	0.995859	0995268	1.096304	0950395	0994601
Log likelihood	3495.092	3494.695	3506.924	3505.850	3507.067
			ARCH-LM test for heteroscedasticity		
statistic	3.627696	3.825191	4.740746	2.473876	3.448986
Prob.	0.6042	0.5748	0.4483	0.7804	0.6311

Notes: * Denotes significance at the 1% level, and ** at 5% level

In the results for the variance equation reported in Tables 5 and 6, the first three coefficients ω (constant), ARCH term (α) and GARCH term (β) for the GARCH (1,1) model are statistically significant and exhibit the expected sign for both markets. The significance of α and β indicates that, lagged conditional variance and lagged squared disturbance have an impact on the conditional variance, in other words this means that news about volatility from the previous periods have an explanatory power on current volatility. Moreover, Table 5 shows that the sum of the two estimated ARCH and GARCH coefficients $\alpha+\beta$ (persistence coefficients) in the GARCH (1,1) model for the KSE is larger than one, suggesting that the conditional variance process is explosive. However, for the CASE returns the sum of the ARCH and GARCH coefficients is very close to one which is required to have a mean reverting variance process, indicating that volatility shocks are quite persistent, but not explosive. Thus, for CASE the findings correspond to those for many developed stock exchanges, while we find a departure for the KSE.

The GARCH-M (1,1) model is estimated by allowing the mean equation of the return series to depend on a function of the conditional variance. From estimation results in Table 5 and Table 6, the estimated coefficient (risk premium) of σ^2 in the mean equation is positive for the two markets, which indicates that the mean of the return sequence depends on past innovations and the past conditional variance. In other words, conditional variance used as a proxy for risk of returns is positively related to the level of returns. These results show that as volatility increases, the returns correspondingly increase with a factor of 0.028 and 0.062 for KSE and CASE, respectively. These results are consistent with the theory of a positive risk premium on stock indices which states that higher returns are expected for assets with higher level of risk. The effect turns out to be significant for CASE.

Furthermore, the asymmetric models EGARCH (1,1) and TGARCH (1,1) are used to investigate the existence of leverage effects in the returns of the KSE and the CASE indices during the study period. The main difference between these two models is that in the EGARCH model, there is no need of nonnegative restriction of the parameters while in the TGARCH model parameters must satisfy the positive condition (Irfan 2010). The asymmetrical EGARCH (1,1) estimated for the returns of the KSE index in Table 5 and the CASE index in Table 6 indicates that all the estimated coefficients are statistically significant at the 1% confidence level. The asymmetric (leverage) effect captured by the parameter estimate γ is also statistically significant with negative sign, indicating that negative shocks imply a higher next period conditional variance than positive shocks of the same sign, which indicates the existence of leverage effects in the returns of the Khartoum stock market index and Cairo and Alexandria Stock Exchange during the study period.

An alternative model to test for asymmetry in KSE and CASE returns is the TGARCH (1,1) model. From estimation results of this model reported in Table 5 and Table 6, the coefficient for the leverage effect is significant and positive for both markets. The significance of this coefficient indicates that negative shocks (bad news) have a larger effect on the conditional variance (volatility) than positive shocks (good news) of the same magnitude.

The other version of asymmetric GARCH model applied in this paper is the (PGARCH). From the results for the PGARCH (1,1) in Table 5 and Table 6, the estimated coefficient γ is significant and positive for the case of Egypt , indicating that positive shocks are associated with higher volatility than negative shocks. In case of Sudan, the estimated coefficient is negative, but insignificant.

The results of diagnostic tests (test for ARCH effects) are reported below the estimation results in Table 5 and Table 6. The ARCH-LM test statistic for all GARCH models (where ARCH and GARCH terms are taken to be of order 1) did not exhibit any additional ARCH effect remaining in the residuals of the models. This shows that the variance equations are well specified for the two markets. (except for the EGARCH (1,1) model for the KSE).

6. Summary and Concluding Remarks

Modelling and forecasting volatility of returns in stock markets has become a fertile field of empirical research in financial markets, because volatility is considered as an important concept in many economic and financial applications like asset pricing, risk management and portfolio allocation.

In this paper we have modeled and estimated stock return volatility in two African markets; the Sudanese stock market (Khartoum Stock Exchange, KSE), and the Egyptian stock market (Cairo and Alexandria Stock Exchange, CASE) by applying different univariate specifications of GARCH type models for daily observations on the index series of each market over the period of 2nd January 2006 to 30th November 2010, as well as describing special features of the markets in terms of trading activity and index components and calculations.

A total of five different models were considered in this paper. The volatility of the KSE and CASE returns have been modelled by using univariate Generalized Autoregressive Conditional Heteroscedastic (GARCH) models including both symmetric and asymmetric models that capture most common stylized facts about index returns such as volatility clustering and leverage effects. These models are GARCH(1,1), GARCH-M(1,1), exponential GARCH(1,1), threshold GARCH(1,1) and power GARCH(1,1). The first two models imply a symmetric effect of past shocks whereas the second group of models allows capturing asymmetric effects. Based on the empirical results presented, the following can be concluded: First, the paper finds strong evidence that daily returns could be characterized by the above mentioned models for the two markets, KSE and CASE data showed a significant departure from normality and the existence of heteroscedasticity in the residuals series. Second, the parameter estimates of the GARCH (1,1) models (α and β) indicate that the conditional volatility of stock returns on the Khartoum Stock Exchange is an explosive process, while it is quite persistent for the CASE index returns series. Third, the parameter describing the conditional variance in the mean equation, measuring the risk premium effect for GARCH-M(1,1), is statistically significant in the two markets, and the sign of the risk premium parameter is positive. The implication is that an increase in volatility is linked to an increase of returns, which is an expected result. Fourth, based on asymmetrical EGARCH (1,1) and TGARCH(1,1) estimation, the results show a significant evidence for the existence of the leverage effects in the two markets, the same result is confirmed only for the CASE by using the PGARCH(1,1) model.

It is left to future research to study in more detail the causes of the structural break in the KSE time series and how it can be taken into account explicitly in the volatility equations. Furthermore, it might be studied to what extent volatility forecasts based on the present models are useful in the context of risk management for the stock markets considered.

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Notes

Note 1. A time series is said to be heteroscedastic if its variance changes over time, otherwise it is called homoscedastic.

Note 2. To mention only a few of the most frequently used: GARCH-M model by Engle, Lilien, and Robins (1987), IGARCH model by Engle and Bollerslev (1986), Exponential GARCH model by Nelson (1991), Threshold GARCH model by Zakoian (1994) and Glosten et al. (1993) and Power ARCH model by Ding et al. (1993).

Note 3. Member states are: Burundi, Comoros, Democratic Republic of Congo, Djibouti, Egypt, Eritrea, Ethiopia, Kenya, Libya, Madagascar, Malawi, Mauritius, Rwanda, Seychelles, Sudan, Swaziland, Uganda, Zambia and Zimbabwe.

Note 4. An investment unit is a proportional accounting share in the total net assets of an open end investment fund (Investment funds are the institutions of collective investment which serve as framework for collection of money funds. Collected money funds are then invested in various assets). The investment unit value is an indicator of how successful a fund is, and the changes of this value depend on the fluctuation of prices of securities and other property that the fund has invested in.

Note 5. Government investment certificates (GICs) are medium-term securities, based on various contracts financed by the Ministry of Finance of Sudan via the *istisna*, *murabaha* and *ijara* tools. Issuance of these *sukuk* is similar to the conventional securitization, where the Ministry of Finance acts as the originator. GICs are based on a limited *mudarabah*, which means that the raised money is invested solely in the projects stipulated in the original contract.

Note 6. The Primary Market deals with the trading of new securities. When a company issues securities for the first time (i.e. IPO), they are traded in the Primary Market through the help of issuing houses, dealing /brokerage firms, investment bankers and or underwriters. The acronym IPO stands for Initial Public Offering, which means the first time a company is offering securities to the general public for subscription. Once the securities (shares) of a company are in the hands of the general public, they can be traded in the Secondary Market to enhance liquidity amongst holders of such financial securities. Thus, the Secondary Market facilitates the buying and selling of securities that are already in the hands of the general public (investors).

Note 7. For more explanations about the ideas of Islamic banking see for example, Venardos (2010).

Note 8. For a detailed discussion of the Islamic Shariaa principles and its practices on stock exchange see for example, El-Gamal (2006) and Ayub (2007).

Note 9. 'Musharakah' is a word of Arabic origin which literally means sharing. In the context of business and trade it means a joint enterprise in which all the partners share the profit or loss of the joint venture. It is an ideal alternative to the interest-based financing with far reaching effects on both production and distribution (Usmani, 1998).

Note 10. For a detailed discussion of the Egyptian Stock Market see for example, Sourial and Mecagni (1999) and Aly, et al. (2004).

Note 11. It is very important to point out that, there might be some bias towards accepting the null hypothesis of a unit root for the index series in level form for the case of Sudan, this simply because of the clear existence of the break points in the series at the end of October 2009 (see Figure1). ADF test fails in case of structural break and it has low power. As one way to account for these structural breaks, Perron (1989) introduced a dummy variable to the ADF test. For a detailed discussion of the structural breaks in unit root test see for example Mills and Markellos (2008). In order to check the robustness of our finding, we repeat the test for KSE for the two subperiods.

Note 12. The main feature of ARCH model is to describe the conditional variance as an autoregression process. However, most empirical time series require using long-lag length ARCH models and a large number of parameters must be estimated. As a potential solution of the problem, GARCH models have been proposed (see Engle and Bollerslev 1986; Nelson 1991) which exhibit higher persistence.

Note 13. Volatility can be defined as a statistical measure of the dispersion of returns for a given security or market index. Volatility can either be measured by using the standard deviation or variance between returns from that same security or market index. Commonly, the higher the volatility, the riskier the security.

Note 14. In the symmetric models, the conditional variance only depends on the magnitude, and not the sign, of the underlying asset return, while in the asymmetric models shocks of the same magnitude, positive or negative, might have different effects on future volatility.

Note 15. This is in contrast to the standard GARCH model where shocks of the same magnitude, positive or negative, have the same effect on future volatility.

Note 16. The model uses zero as its threshold to separate the impacts of past shocks. Other threshold can also be used; see (Tsay, 2010) for the general concepts of threshold models.

Note 17. For potential issues regarding the numerical solution of the maximum likelihood estimators for GARCH models, the interested reader might consult Maringer and Winker (2009).

Note 18. If the variance equation of GARCH model is correctly specified, there should be no ARCH effect left in the residuals.

Appendix. Estimation results of different GARCH models for Khartoum stock exchange (Sub-periods)

Coefficients	**GARCH (1,1)**		**GARCH-M (1,1)**		**EGARCH (1,1)**		**TGARCH (1,1)**		**PGARCH (1,1)**	
	First sub-period	Second sub-period	First sub-period	Second sub-period	First sub-period	Second sub-period	First sub-period	Second sub-period	First sub-period	Second sub-period
Mean equation										
μ	0.000192	-1.18E-05	-0.002410*	-7.09E-05*	0.000572*	-1.90E-05	7.72E-05	-2.18E-05	0.000128	-1.31E-05
λ			0.282394*	0.127631*						
Variance equation										
ω	3.52E-05*	6.00E-08*	3.70E-05*	6.05E-08*	-3.952504*	-1.581487*	3.55E-05**	5.82E-08**	8.64E-07	4.01E-08
α	0.739287*	0.124267*	0.714649*	0.128282*	0.862935*	0.171235*	0.487554**	0.083005**	0.865**	0.122**
β	0.406875*	0.650981*	0.377463*	0.646581*	0.605742*	0.900153*	0.399900**	0.657500**	0.327**	0.640**
γ					-0.127306*	-0.123552*	0.524922**	0.086663*	0.190**	0.058**
δ									2.794**	2.057**
$\alpha + \beta$	1.146162	0.775248	1.092112	0.774863	1.468677	1.071388	0.887454	0.740505	1.192	0.762
Log likelihood	3303.647	1627.045	3309.044	1627.207	3309.860	1608.297	3307.803	1627.809	3307.977	1636.926
ARCH-LM test for heteroscedasticity										
statistic	0.171356	3.341550	0.120292	2.982367	0.205917	0.901964	0.151712	1.741300	0.161	2.633
Prob.	0.9994	0.6475	0.9997	0.7027	0.9990	0.9701	0.9995	0.8837	0.999	0.756

* and ** indicate significant at 5% and 1% respectively.